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Why do mobile consumers resist mobile commerce applications? A hybrid fsQCA-ANN analysis

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A R T I C L E I N F O

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A B S T R A C T

Since its inception, mobile commerce (m-commerce) has introduced many disruptive changes to the business world via various types of m-commerce applications, which refer to the novel applications of m-commerce in conducting tasks that require mobility, for instance, mobile payment and mobile shopping. In view that not all mobile consumers around the world are keen to adopt mobile commerce applications, this study seeks to clarify the roles of active innovation resistance barriers (comprising functional and psychological barriers) on three distinct forms of resistance behaviour exhibited by mobile consumers (i.e., rejection, postponement, or opposition) towards m-commerce applications through the theoretical lens of Innovation Resistance Theory. For this purpose, an asymmetric and non-linear model was built and analysed through a configurational approach complemented by machine learning. The results indicate that all active innovation resistance barriers matter but are not equally important in triggering the resistance behaviours. Theoretically, this study has advanced the Innovation Resistance Theory and enriched the existing literature on m-commerce applications resistance. Practically, to lower the resistance behaviours of mobile consumers towards m-commerce applications, practitioners are advised to prioritise strategies that could overcome the psychological barriers.

1. Introduction

The rising penetration rate of smart mobile devices and advances in high-speed mobile internet have reshaped consumers' experiences and habits in recent years (Luceri et al., 2022). In addition, the COVID-19 pandemic has somehow induced consumers to embrace mobile commerce (m-commerce) and subsequently accelerated the proliferation of m-commerce (Katsumata et al., 2022). Although m-commerce is often viewed as a subset of electronic commerce (e-commerce), there is a distinguished feature of m-commerce namely mobility, a key feature that allows mobile consumers to engage in a transaction anywhere (Almeida Lucas et al., 2023). Further, given that it is easy to detect the current locations of mobile consumers through smart mobile devices, m-commerce can provide highly personalised services and information to mobile consumers compared to e-commerce (Haque and Wong, 2022). With this, the global m-commerce sales volume is projected to reach USD4.5 trillion in 2024 (Insider Intelligence, 2022).

Ever since its emergence, m-commerce has introduced disruptive changes to the business world (Buhalis et al., 2023) via various types of m-commerce applications (Omar et al., 2021), a term that is defined by Al Janabi and Hussein (2020) as novel applications of m-commerce in conducting tasks that require mobility, for instance, mobile shopping. As identified by scholars (Du and Li, 2019; Hew, 2017; Turban et al., 2018), there are numerous emerging m-commerce applications, such as mobile payment, mobile ride-hailing, mobile banking, etc.

Despite the advantages, not every mobile consumer is keen to adopt m-commerce applications, resulting in resistance to m-commerce applications (Kaur et al., 2021). For example, Chaouali and Souiden (2019) reported that French mobile consumers resist mobile banking, while Zhu et al. (2022) observed a low adoption rate of mobile payment in Thailand. Furthermore, the same phenomenon is reported worldwide for different classes of m-commerce applications, as noted in Appendix A. This suggests that the resistance to m-commerce applications is a worldwide issue that warrants further investigation. Understanding the innovation resistance behaviours among non-adopters in the business world is crucial in reducing innovation failures (Ma and Lee, 2020). Given that innovation is referred to as "an idea, practice, or object perceived as new by an individual or other unit of adoption" (Rogers, 2010, p.11), m-commerce applications are considered an innovation (Chhonker et al., 2018) whose success or failure dramatically depends

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upon the resistance behaviours of mobile consumers. According to innovation resistance scholars, these resisting non-adopters could either reject, postpone, or oppose the adoption of m-commerce applications (Talwar et al., 2020). If these complicated resistance behaviours towards m-commerce applications are not comprehensively explored, this will cause an m-commerce application to fail in the market (Khaw et al., 2022). Hence, it is crucial to understand why mobile consumers resist m-commerce applications, especially from the perspective of their varied resistance behaviours.

Thus far, scholars have been devoting their efforts to understanding the non-adoption of or resistance to m-commerce applications. Nevertheless, as established in Appendix B, these past studies simplistically conceptualised the behaviours of mobile consumers who are resistant to m-commerce applications, as the commonly used key endogenous constructs in these studies were only resistance and intention to adopt or use. This is insufficient as the complicated resistance behaviours of mobile consumers towards m-commerce applications are usually manifested in three distinct forms, namely rejection, postponement, or opposition (Talwar et al., 2020) and, therefore, it should not be assumed that all mobile consumers would exhibit the same resistance behaviour.

On top of that, these past studies mainly engaged structural equation modelling (SEM) and regression in analysing the data. It should be noted that these regression-based methods[1] have limitations, one of which is that a symmetric and linear relationship is assumed between two constructs in a regression model (Diwanji, 2022). A symmetric relationship assumes that a high level of an exogenous construct (X) is both sufficient and necessary in causing a high level of an endogenous construct (Y) and vice versa (Olya and Altinay, 2016). However, it is possible that Y (i.e., the outcome) would still occur even if X (i.e., the condition) were absent, implying that X is a sufficient but not a necessary condition for Y to occur (Pappas et al., 2019). In this manner, a low level of X may not always lead to a low level of Y, possibly due to the presence of other exogenous constructs (Pappas and Woodside, 2021).

Conversely, an asymmetric relationship contends that a high level of Y could be contributed by either a low or a high level of X due to its possible combinations with other exogenous constructs (Gligor and Bozkurt, 2020). As such, using symmetric methods (e.g., regression-based methods) is insufficient for researchers to fully understand the asymmetric relationships between constructs, especially in real-world consumer research (Diwanji, 2022). To address this, researchers should engage fuzzy set qualitative comparative analysis (fsQCA), a configurational approach that has the ability to handle the asymmetric relationships between constructs and identify all necessary and/or sufficient conditions that lead to a specific outcome (Gligor and Bozkurt, 2020; Hossain et al., 2022a). Besides, the fsQCA could handle non-linear relationships (Pappas and Woodside, 2021) that suggest a unit of change in X would not always result in a constant change in Y (Hew et al., 2018). This is crucial, as linear relationships, which assume a straight-line relationship among constructs, tend to oversimplify the complicated decision-making process of consumers (Leong et al., 2020a).

Although the fsQCA has the advantages described above and can derive various configurations of conditions that lead to a specific outcome, it could not rank the causal conditions according to their importance to the outcome (Li et al., 2022). To address this shortcoming, Aw et al. (2023) recommended the use of artificial neural network (ANN) analysis in ranking the causal conditions through a sensitivity analysis. Based on the above arguments, this study adopts a hybrid analysis approach that complements the fsQCA with ANN analysis. It should also be noted that the ANN analysis is suitable for both non-linear and asymmetry models (Hanafizadeh et al., 2010), making it the right choice in complementing the fsQCA.

[1] According to Hult et al. (2018), SEM is considered a type of regression-based analysis method.

To address the literature gaps established above, this study builds an asymmetric and non-linear model through the theoretical lens of Innovation Resistance Theory to clarify the three distinct forms of resistance behaviour exhibited by mobile consumers towards m-commerce applications. A hybrid analysis that combines fsQCA and ANN analysis will be employed to achieve this study's purpose. Theoretically, this study advances the Innovation Resistance Theory by serving as one of the pioneers in scrutinising the Innovation Resistance Theory through a hybrid fsQCA-ANN approach. Moreover, this study enriches the existing literature on m-commerce applications resistance by understanding the complicated resistance behaviours of mobile consumers (i.e., rejection, postponement, or opposition) through a configurational approach complemented by machine learning.

In the following sections, a literature review will be conducted for m-commerce applications and Innovation Resistance Theory, guiding the development of the research model. Afterwards, the research methodology would be disclosed prior to the results yielded from the hybrid analysis. A general discussion and their implications would then be offered in light of the results. Lastly, this study concludes with the study's limitations and relevant recommendations.

2. Literature review

2.1. M-commerce applications

The extant literature agreed that m-commerce applications could offer value-added features such as mobility, broad reach, ubiquity, convenience, instant connectivity, and personalisation to consumers (Dastane et al., 2020; Eze and Poong, 2013; Ghazali et al., 2018; Hew, 2017). These features allow businesses to provide customisable products or services to consumers based on their preferences, current location, and time (Abu-Shanab and Ghaleb, 2012), which can be seen in mobile food delivery that presents a list of available food and beverages located nearby to the consumers based on their current location and time. Moreover, m-commerce applications have been evolving to better support business processes in an efficient manner (Chhonker et al., 2017; Hadiana, 2016), especially when the features of smart mobile devices have advanced significantly in recent years (Oliveira et al., 2014). For instance, the thumbprint scanner on smart mobile devices accelerates the speed of making payments through mobile payment as consumers do not need to key in the pin code (Desmal et al., 2019).

Other than assisting consumers in performing certain tasks that require mobility (Al Janabi and Hussein, 2020), m-commerce applications aim to facilitate the realisation of commercial transactions, or potential ones, under the m-commerce environment (Benou et al., 2012; Benou and Vassilakis, 2010). Therefore, this study regards m-commerce applications as a means for consumers to conduct tasks that require mobility, which would subsequently introduce potential business transactions and perhaps facilitate businesses to realise the transactions eventually. Thus far, many m-commerce applications already accommodate a broad range of business functions and processes (Naicker and Merwe, 2018). Accordingly, this study only covers several popular classes of m-commerce applications based on the top 100 free mobile apps in both App Store and Google Play (Turban et al., 2015, 2018). Derived from App Annie (2020), the top 100 free mobile apps on both platforms are organised according to their classes in Appendix C. In total, there are 14 classes of m-commerce applications identified.

2.2. Innovation Resistance Theory

According to Heidenreich et al. (2016), one major reason for many innovations to fail in the market is due to the resistance of consumers. The adoption of innovation, as opined by Laukkanen et al. (2009), would only begin if consumers could overcome their resistance to innovation. That is to say, there would always be a certain extent of innovation resistance before the adoption decision (Heidenreich and

Spieth, 2013). To this extent, innovation resistance is defined as the "resistance offered by consumers to changes imposed by innovations" (Laukkanen, 2016, p.2432). Given the possibility that innovations impose changes on consumers who might respond negatively by resisting the changes, Ram (1987) crafted the Innovation Resistance Theory to explain the resistance behaviours of consumers. Ram and Sheth (1989) then refined the theory and posited that during the innovation resistance phase, consumers are usually facing several barriers that directly inhibit their adoption intentions, and these barriers could be categorised into functional barriers and psychological barriers. Since its emergence, the Innovation Resistance Theory has been serving as a practical framework for scholars to understand the resistance to different types of innovation (Leong et al., 2021). Other than being widely employed by scholars to understand the resistance to different m-commerce applications (such as the ones identified in Appendix B), the Innovation Resistance Theory has been employed to explain the resistance to internet banking (Matsuo et al., 2018), retail drone delivery services (Sham et al., 2023), massive open online courses (Ma and Lee, 2019), and many more.

According to several innovation resistance scholars (Laukkanen, 2016; Lian and Yen, 2013), functional barriers comprise usage barrier, value barrier, and risk barrier, while psychological barriers are made up of tradition barrier and image barrier. Usage barrier would arise if an innovation causes inconvenience to the existing practices or workflows, which subsequently leads to usage problems instead of convenience (Leong et al., 2020b). Value barrier, on the other hand, arises if consumers opine that an innovation does not offer a relative advantage after they have compared it with existent alternatives, as consumers will not accept an innovation unless it offers relative advantages that could not be offered by the alternatives (Joachim et al., 2018). Moreover, during the assessment of an innovation, consumers are often unsure if the innovation is matured and functional as promised. This subsequently gives rise to the risk barrier, which refers to the degree of risks an innovation entails (Heidenreich and Spieth, 2013). While functional barriers mainly concern innovation functions, psychological barriers mainly deal with the psychological conflicts that developed from a consumer's beliefs (Joachim et al., 2018). Tradition barrier comes into play when an innovation is perceived to be conflicting with the consumers' family values, social norms, or entrenched traditions (Joachim et al., 2018), while image barrier emerges from the consumers' negative or bad impressions of the side effects of an innovation (Hew et al., 2019).

Despite many theories that could be employed to understand the behaviours of mobile consumers towards m-commerce applications, for instance, the Diffusion of Innovations Theory (Rogers, 2003), Technology Acceptance Model (Davis, 1989), and Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003, 2012), these theories are mainly employed to understand the drivers of adoption behaviours (Hew et al., 2015). Owing to innovation adoption and innovation resistance are two distinct concepts and do not share the same drivers (Sun et al., 2022), this study mainly adopts the Innovation Resistance Theory as the theoretical lens to understand the resistance behaviours of mobile consumers towards m-commerce applications, as the main objective of Innovation Resistance Theory is to understand the major barriers that would cause consumers to develop resistance to innovations (Leong et al., 2021).

3. Research model

Drawing upon the Innovation Resistance Theory, this study develops the research model (as shown in Fig. 1) which mainly comprises usage barrier, value barrier, risk barrier, tradition barrier, and image barrier. Together, these barriers trigger consumers' negative attitudes towards an innovation after deliberately evaluating it (Talke and Heidenreich, 2014). Although some innovation resistance scholars opined that the innovation-specific functional barriers and psychological barriers shall

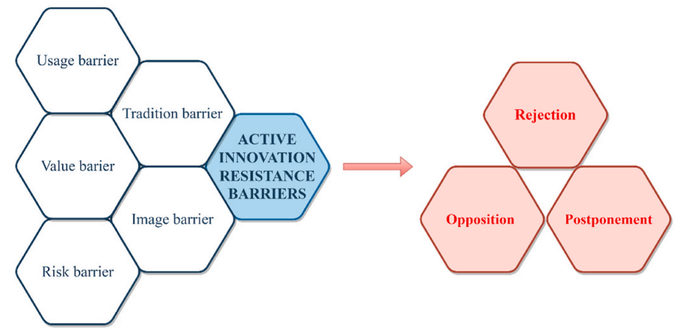


Fig. 1. The research model.

encompass a wider range of barriers, for example, visibility barrier and information barrier (Joachim et al., 2018; Talke and Heidenreich, 2014), this study adopts only usage barrier, value barrier, risk barrier, tradition barrier, and image barrier as these barriers have been consistently employed to study the resistance to different m-commerce applications (as discovered in Appendix B). In this manner, these barriers have proven their applicability and suitability across different m-commerce applications.

Specifically, in a mobile ticketing study conducted by Chen et al. (2022), all the active innovation resistance barriers identified in Fig. 1 were found to be inhibitors that reduce the usage intention of mobile ticketing, whereas usage barrier, value barrier, and risk barrier were discovered to have negative associations with the usage intention of mobile payment by Kaur et al. (2020). Besides, Yu and Chantatub (2016) revealed that both functional barriers (usage barrier, value barrier, and risk barrier) and psychological barriers (tradition barrier and image barrier) were significantly impacting the intention to resist mobile banking in Thailand and Taiwan. Similarly, Leong et al. (2020b) discovered that except for image barriers, all the active innovation resistance barriers adopted in this study were positively related to the resistance of mobile payment. In another study of mobile payment, Khanra et al. (2021) observed that the postponement of mobile payment was the result of usage and image barriers. On the other hand, usage and image barriers were found to be the drivers of rejection behaviour, while value barrier was leading to postponement behaviour in Chen et al. (2019)'s study of branded apps resistance. In view of these relevant past studies, it is believed that the active innovation resistance barriers adopted in this study would ultimately lead to three distinct forms of resistance behaviour, namely rejection, postponement, or opposition (Talwar et al., 2020).

Among the forms of resistance behaviour, rejection is the most extreme form (Mzoughi and M`Sallem, 2013) as rejecters would never adopt the innovation (Chen et al., 2019). On the other hand, postponers would postpone the adoption decision until the right time (Park and Koh, 2017), which is usually within a year (Laukkanen et al., 2008). Although postponers find the innovation acceptable now, they would like to wait for it to improve further before adopting it (Chen et al., 2019). Besides, opponents would actively attack the innovation by telling negative word-of-mouth to stop its diffusion as they are not confident with it right now (Chen et al., 2019; Mzoughi and M'Sallem, 2013). Nevertheless, opponents are still willing to seek further information about the innovation before finalising their decisions, and sometimes they will directly accept the innovation if they are persuaded by the latest information obtained (Cornescu and Adam, 2013). Hence, opponents intend to adopt an innovation but have yet to decide when, certainly not within a year (Lian and Yen, 2013).

4. Methodology

4.1. Data collection

The data for the hybrid analysis was collected from Malaysian mobile consumers who are resisting one of the m-commerce applications identified in Appendix C. It is believed that the Malaysian mobile consumers are a suitable target population for the purpose of this study as the adoption rate of m-commerce applications is not encouraging in Malaysia (Leong et al., 2020b; Ooi et al., 2021) despite that the country has reached 144% mobile penetration rate (Malaysian Communications and Multimedia Commission, 2022). For instance, in a national survey conducted by the Malaysian Communications and Multimedia Commission (2021), it was revealed that less than half of the Malaysian mobile consumers were using mobile payment (41%), mobile banking (38.9%), and mobile shopping (41.1%).

To obtain representative samples from the target population, quota sampling was employed to allocate quotas to five major geographical regions in Malaysia (Hew et al., 2017). The quotas were established based on the number of mobile subscriptions in order to ensure a fair representation of samples (Malaysian Communications and Multimedia Commission, 2020). Specifically, 350 targeted samples or quotas were assigned to the five major geographical regions for each resistance behaviour based on their number of mobile subscriptions, making the total targeted samples or quotas 1050 in this study. As suggested by Salman et al. (2022), the minimum required sample size was calculated via G*Power (using the setting of effect size: 0.15, probability of error: 0.05, power: 0.80, and number of predictors: five), and the result suggests that each form of resistance behaviour would require a sample size of 92. Given this, it is believed that the targeted samples of 350 for each resistance behaviour were sufficient for this study.

Before the actual data collection, a pre-test involving three expert researchers in the relevant fields and a pilot test comprising 25 samples from each resistance behaviour were conducted to identify potential issues during the data collection. It should be noted that all samples recruited during the pilot test were omitted from the final sample.

To reach out to the respondents, an online survey questionnaire was posted in an online English forum named "lowyat.net" (lowyat.net, 2020), the top forum in Malaysia in terms of its traffic rank (Alexa, 2020). To encourage participation, cash vouchers were offered as lucky draw prizes (Degirmenci, 2020). Besides, to identify qualified respondents, three screening questions namely (i) nationality, (ii) number of smart mobile device(s) owning, and (iii) unadopted m-commerce application (respondents were asked to identify one of the 14 classes of m-commerce applications shown in Appendix C), were asked at the beginning of the online questionnaire. The participants who are not Malaysian, do not own any smart mobile devices, or do not resist to any of the given m-commerce applications, were thanked and dismissed.

Given that the qualified respondents would have shown three distinct types of resistance behaviours, the online questionnaire then asked about their future intention to adopt their resisting m-commerce application. The qualified respondents who chose "never", "intend to use, most likely within a year from now", and "intend to use but have not decided when, most likely more than a year from now" were grouped as rejecters, postponers, or opponents respectively (Chen et al., 2019; Laukkanen et al., 2008). Subsequently, the qualified respondents were guided to the relevant measurement items (as shown in Appendix D) to provide their opinions via a Likert-scale that has seven points, ranging from strongly disagree (represented by point one) to strongly agree (represented by point seven). For the purpose of improving data quality, one attention-trap question (i.e., "Please select '6 - Agree' for this statement") was designed to appear in the middle of the online questionnaire (Gong et al., 2020; Lee et al., 2021).

In total, there were 1311 respondents participated in the online survey. However, 98 of them were not qualified respondents and, therefore, did not proceed to answer the remaining sections of the online questionnaire. Among the 1213 qualified respondents, 58 were excluded from the final sample as they failed to answer the attention-trap question correctly, resulting in 1155 qualified and valid responses. Given that meeting all the quotas established for each resistance behaviour is necessary, the online questionnaire continued even when some of the required quotas were met, resulting in 105 excessive responses eliminated from the final sample. Ultimately, the final sample constitutes 1050 qualified and valid responses. Besides, since all the questions were required to be answered and the online survey platform would only record complete responses, there were no missing values in the final sample, whose demographic statistics are presented in Appendix E.

The final sample is believed to exhibit high representativeness of the target population, as the distribution patterns of some demographic statistics are comparable to a national survey on hand phone users (Malaysian Communications and Multimedia Commission, 2021). Firstly, the respondents in both surveys were mainly youngsters, and the percentage of elders gradually reduces as the age group increases. Secondly, the respondents in both surveys indicated they received at least secondary education and above. Thirdly, both surveys reveal that the respondents earn a monthly income of RM3000 (approximately USD640 at the time of writing) or below.

4.2. Data analysis techniques

As discussed earlier, this study engages a hybrid analysis design in which the fsQCA is conducted prior to the ANN analysis. Specifically, different combinations (also known as configurations) of conditions (i.e., exogenous constructs) that lead to a specific outcome (i.e., endogenous construct) would first be obtained from the fsQCA (Pappas and Woodside, 2021), then the necessary and/or sufficient conditions would be fed as input neurons to the ANN analysis in order to rank these conditions based on their relative importance with respect to a specific output neuron (i.e., endogenous construct), just as Aw et al. (2023) recommended. The following sub-sections discuss the steps involved in both analyses. In simple terms, the fsQCA would first reveal the possible combinations of active innovation resistance barriers that could result in high rejection, postponement, or opposition. Afterwards, the ANN analysis would attempt the rank the resistance barriers based on their importance to the resistance behaviours of rejection, postponement, or opposition.

Prior to the hybrid analysis, a test of linearity using ANOVA was performed for the relationships between constructs to establish the existence of non-linear relationships between constructs (Ooi et al., 2018b). Both common method bias and non-response bias were also assessed (Lou et al., 2022), but this study did not detect and clear outlier cases given that the fsQCA could capture and handle the impact of outlier cases (Gligor et al., 2022). Besides, as advised by Pappas and Woodside (2021), evaluating all constructs' reliability and validity before the hybrid analysis is crucial. In quantitative research, it is important to confirm whether a construct could consistently and accurately represent and measure the concept it represents, and consistency is assessed thrugh reliability, while accuracy is verified via validity (Hair et al., 2016). Henceforth, following Hair et al. (2022), this study evaluates internal consistency reliability, convergent validity, and discriminant validity respectively using ρA reliability metric, average variance extracted (AVE), and heterotrait-monotrait ratio (HTMT) of correlations. It should also be noted that where applicable, all tests were two-tailed as non-directional hypotheses were being tested (Hair et al., 2016).

4.2.1. fsQCA

To conduct the fsQCA, it is necessary to first calibrate and transform the collected data into fuzzy values that fall in between zero (representing full non-membership) and one (representing full membership) using the direct calibration method (Mattke et al., 2022). Since there are several measurement items for a construct, this study follows Gligor et al. (2022) who suggested that all scores for the measurement items of a single construct should be averaged into a single score. Afterwards, during the calibration step, the values of six, four, and two were respectively used as the thresholds for full membership, crossover point, and full non-membership since a seven-point Likert-scale was used for all measurement items (Park et al., 2020). Given that the fuzzy value of 0.50 represents the crossover or maximum ambiguity point, Mattke et al. (2022) advocated that researchers add a constant of 0.001 to all 0.50 fuzzy values during the data calibration to retain these values for further analysis.

After the data calibration, a necessity analysis should be conducted in order to identify which condition has to exist (i.e., necessary) for a specific outcome of interest to occur (Mattke et al., 2022). In this step, Nikou et al. (2022) advised that it is crucial to discover if a high level or a low level of a condition is necessary for a specific outcome because in an asymmetric analysis, it could not be assumed that if a high level of a condition is necessary then its opposite (i.e., low level) is unnecessary. To identify the necessary conditions, this study assesses all consistency, coverage, and relevance of necessity (RoN) scores, which have to exceed 0.90, 0.50, and 0.60 respectively (Hossain et al., 2022b; Mattke et al., 2022).

On top of analysing the necessary conditions, it is required to conduct a sufficiency analysis that identifies all sufficient configurations that induce a specific outcome through the construct of truth table (Nikou et al., 2022). At first, the truth table showcases all potential configurations that induce a specific outcome but some of them are not really sufficient in inducing the outcome, hence it is important to use frequency, raw consistency, and proportional reduction in inconsistency (PRI) thresholds to obtain the qualified and sufficient configurations (Mattke et al., 2022). In this study, given that the sample size for each resistant behaviour is above 150 cases, the frequency threshold was set at the value of three (Pappas and Woodside, 2021). Furthermore, the raw consistency threshold was set at 0.75 or more, while the PRI threshold was specified at 0.50 or more (Hossain et al., 2022b).

Once the truth table is constructed and filtered, the Quine-McCluskey algorithm would be used to minimise the number of sufficient configurations so that a more manageable solution could be obtained for reporting purposes (Mattke et al., 2022). The Quine-McCluskey algorithm generally returns three types of solutions: complex, parsimonious, and intermediate (Aw et al., 2023). The intermediate solution forms part and parcel of the complex solution and contains the parsimonious solution, hence comparing the parsimonious and intermediate solutions could discover more insights as to which conditions are core and peripheral to the outcome of interest (Pappas and Woodside, 2021). Particularly, conditions that appear in both parsimonious and intermediate solutions are known as the core conditions which have a stronger causal relationship with the outcome, whereas conditions that only appear in the intermediate solution are called peripheral conditions (Park et al., 2020).

In addition, according to Pappas and Woodside (2021), it is crucial to perform a test of predictive validity, which unveils the quality of solutions in predicting the outcomes of interest with additional samples. Specifically, the full sample is randomly split into a subsample and a holdout sample at first, then the same fsQCA as described above would be performed for the subsample (Pappas et al., 2016). Afterwards, the findings obtained from the fsQCA shall be tested against the holdout sample (Pappas and Woodside, 2021).

4.2.2. ANN analysis

From the fsQCA, the conditions (i.e., usage barrier, value barrier, risk barrier, tradition barrier, and image barrier) that lead to the outcomes (i.e., rejection, postponement, and opposition) were identified in the solutions obtained for each type of resistance behaviour and subsequently would be fed as the input neurons in the ANN analysis (Aw et al., 2023). Hew et al. (2017) opined that ANN resembles a modelling technique that mimics human neural systems; hence ANN is able to acquire new knowledge by learning. With this learning ability, ANN is trainable to strengthen its performance (Leong et al., 2019). A typical multi-layer perceptron ANN comprises input, hidden, and output layers (Hew et al., 2019). Within each layer, there are neuron nodes connecting to each other via synaptic weights, which are to be altered during the learning process via a non-linear activation function to achieve the targeted objectives (Lee et al., 2020). In this manner, a deeper learning process would yield more accurate results and, therefore, this study follows Leong et al. (2023) to design an ANN architecture with two hidden layers.

In performing the ANN analysis, the feed-forward back-propagation algorithm was engaged as this particular algorithm manages to minimise errors during the deep learning process (Ooi et al., 2018a). Also, to prevent the over-fitting issue, Leong et al. (2019) suggested the use of a 10-fold cross-validation method in which the data training and data testing ratio is at 9:1. In addition, the non-linear activation function was set to sigmoid, whereas the hidden neurons within the hidden layers were automatically computed by the ANN analysis (Hew et al., 2018). It is also important to assess the predictive accuracy of the ANN analysis, and Ooi et al. (2018b) recommended the use of root mean squared error (RMSE) values, which are computed from the sum of square errors (SSE) and have to be of small magnitude in order to reflect an excellent prediction accuracy. In addition, this study follows a goodness-of-fit index (R^2) suggested by Leong et al. (2020a) in further assessing the predictive accuracy. Thereafter, the input neurons could be ranked in terms of their relative importance to the output neurons through the sensitivity analysis (Lee et al., 2020). In this study, given that there are three distinct types of resistance behaviour, a total of three deep learning ANN models were built accordingly.

5. Results

5.1. Test of linearity

As shown in Table F1, Table F2, and Table F3, if the deviation from linearity is statistically significance at $p < 0.10$, then there is a non-linearity between a pair of constructs (Ooi et al., 2018b). The ANOVA test reveals that for each resistance group, there exists at least one non-linear relationship among the constructs, and the group of postponers has the most non-linear relationships. With this, it is ascertained that both fsQCA and ANN analysis are suitable for analysing the relationships among constructs for each resistance group.

5.2. Common method bias

To control for common method bias, both procedural controls and statistical remedy were implemented during and after the data collection stage respectively (Kock et al., 2021). Specifically, the procedural controls implanted during the data collection stage were (i) recruiting qualified respondents who are relevant to this study, (ii) using clear and concise language throughout the online questionnaire, and (iii) assuring respondents of their anonymity and the confidentiality of their responses (MacKenzie and Podsakoff, 2012). As for the statistical remedy, this study follows Kock (2015)'s full collinearity assessment approach to assess the severity of common method bias. The results indicate that the variance inflation factors range from 1.106 to 2.572 for all groups of resistance behaviour, supporting that common method bias shall not be a serious concern in this study as variance inflation factors are all below the conservative threshold of 3.30 (Hair et al., 2022).

5.3. Non-response bias

To assess the non-response bias, a Chi-square test was performed to test whether there is a significant difference between early and late responses in terms of demographic variables (Hew et al., 2019). The results indicate no significant difference between these groups, so non-response bias should not be a concern in this study (Lou et al., 2022).

5.4. Reliability and validity

The reliability and validity tests' results for each group of behaviour are displayed in Table G1, Table G2, and Table G3 accordingly. Given that the ρA reliability metric of all constructs are above the threshold of 0.70, the internal consistency reliability could be established for all resistance groups (Hair et al., 2019). Moreover, the AVE values are all beyond 0.50, indicating the establishment of convergent validity for all groups (Ghasemy et al., 2020). For the discriminant validity, since the HTMT of correlations for both rejecters and opponents are all below the limit of 0.90, the constructs are discriminable from each other (Benitez et al., 2020). However, for the postponers, there are some HTMT of correlations surpassing the limit of 0.90, raising doubts about the discriminant validity. As such, bias-corrected 95% confidence intervals were further calculated and presented in Table G2 in order to support the discriminant validity (Hair et al., 2020). Specifically, if the value of one is not included in the confidence intervals, then it could be ascertained that the HTMT of correlations are statistically smaller than one, hence supporting the discriminant validity (Hair et al., 2019). Given that all constructs in the three resistance groups have passed the reliability and validity tests, the following sections present the results obtained from the hybrid fsQCA-ANN analysis.

5.5. fsQCA

Table 1 presents the necessity analysis for high levels of rejection, postponement, and opposition. The results suggest that none of the conditions, whether at high or low levels, are necessary to induce a high level of rejection, postponement, or opposition.

Afterwards, Table 2 details the solutions obtained from the Quine-McCluskey algorithm for each resistance group. In every solution, it is noted that at least one sufficient configuration could lead to a high level of outcome. Specifically, there are a total of six and eight configurations that would accordingly lead to a high rejection and high postponement, whereas there is only one configuration that induces a high opposition. These configurations are considered sufficient, as their consistency and raw coverage values are at least 0.75 and 0.20 (Hossain et al., 2022b). Overall, these solutions are highly consistent in predicting the outcomes of interest, as the solution consistency values are respectively reported at 0.802, 0.885, and 0.864 for rejecters, postponers, and opponents (Yang et al., 2023). Moreover, the overall solution coverage values are recorded at 0.929, 0.764, and 0.543, suggesting that a substantial proportion of rejection, postponement, and opposition is covered by the solutions yielded (Pappas and Woodside, 2021).

Subsequently, the predictive validity test described by Pappas and Woodside (2021) is presented in Appendix H. In a particular manner, the same fsQCA was performed on the subsample, and the solutions for all resistance groups are listed in Table H1. Afterwards, all configurations obtained were tested against the holdout sample using the XY plot (a sample is showcased in Figure H1), which will then give the consistency and raw coverage scores. These scores were then compared with the scores obtained from the subsample in Table H2. Since the scores do not differ much in both subsample and holdout sample, the predictive validity of data in this study is confirmed.

Besides, given that all conditions appear in at least one of the configurations among all three solutions (i.e., none of the conditions is identified as "don't care" across all configurations), hence these conditions, or known as the exogenous constructs, are subsequently fed in the subsequent ANN analysis as input neurons for all three types of resistance behaviour. Specifically, usage barrier, value barrier, risk barrier, tradition barrier, and image barrier would all be included in the subsequent ANN analysis, which has the ability to rank these exogenous constructs in terms of their relative importance to a specific endogenous construct (i.e., rejection, postponement, or opposition).

5.6. ANN analysis

As displayed in Fig. 2, three deep learning ANN models were built for each resistance behaviour with the active innovation resistance drivers as the input neurons. These ANN models have a powerful predictive accuracy according to Table 3, given that their RMSE values are of small magnitude during both training and testing stages. In addition, the R^2 values of these models indicate that 74.4%, 72.2%, and 77.3% of rejection, postponement, and opposition are predicted by the ANN models, indicating a great level of predictive accuracy.

Owing to the great level of predictive accuracy displayed by the ANN models, Table 4 shows the sensitivity analysis performed for ANN models. In ANN Model A, the most important input neuron for the output neuron of rejection seems to be tradition barrier, and the same applies to the output neuron of postponement in ANN Model B. For the output neuron of opposition, ANN Model C indicates that image barrier is the input neuron with the highest relative importance.

6. Discussions and implications

6.1. General discussions

The fsQCA reveals that all active innovation resistance barriers are present in at least one of the configurations for each resistance behaviour. Also, none of the barriers emerges as a necessary condition or plays no influence (i.e., "don't care" situation) among all resistance groups. This indicates that every barrier matters in causing the resistance behaviours, supporting and resonating with the Innovation Resistance

Table 1
The necessity analysis.

Conditions	High level of rejection			High level of postponement			High level of opposition		
	Consistency	Coverage	RoN	Consistency	Coverage	RoN	Consistency	Coverage	RoN
TB	0.946	0.784	0.588	0.704	0.897	0.908	0.830	0.581	0.718
~TB	0.238	0.640	0.900	0.559	0.694	0.761	0.563	0.370	0.598
IB	0.822	0.865	0.830	0.622	0.889	0.920	0.708	0.741	0.890
~IB	0.398	0.634	0.805	0.601	0.674	0.706	0.666	0.334	0.418
UB	0.702	0.877	0.888	0.644	0.895	0.921	0.710	0.679	0.850
~UB	0.527	0.676	0.760	0.597	0.684	0.723	0.688	0.361	0.462
VB	0.733	0.887	0.890	0.633	0.885	0.914	0.700	0.702	0.868
~VB	0.501	0.665	0.766	0.603	0.689	0.724	0.690	0.353	0.441
RB	0.838	0.842	0.788	0.692	0.868	0.883	0.765	0.572	0.738
~RB	0.395	0.676	0.840	0.554	0.698	0.869	0.611	0.379	0.572

Notes:
1. IB = image barrier, OP = opposition, PP = postponement, RB = risk barrier, RJ = rejection, TB = tradition barrier, UB = usage barrier, and VB = value barrier.
2. Conditions with a tilde (~) indicate conditions in their low level.

Table 2
Solutions that lead to high levels of outcomes.

Conditions	High level of rejection						High level of postponement								High level of opposition
	Configurations						Configurations								Configurations
	RC1	RC2	RC3	RC4	RC5	RC6	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	OC1
Tradition barrier	☑	☑	☑	☑			☑	☑	☑		×			×	✓
Image barrier			✓		×	✓	×	☑		☑	×	☑	×	×	☑
Usage barrier		×			☑	☑	×			×	☑	☑	×		☑
Value barrier	×				×	✓			✓	×	×	✓	×	×	☑
Risk barrier				✓	✓	✓		☑	☑	×		☑	☑	☑	☑
Consistency	0.800	0.799	0.888	0.871	0.900	0.945	0.922	0.938	0.944	0.930	0.935	0.943	0.912	0.897	0.864
Raw coverage	0.481	0.507	0.804	0.812	0.248	0.601	0.333	0.547	0.557	0.241	0.266	0.522	0.305	0.294	0.543
Unique coverage	0.002	0.008	0.026	0.031	0.006	0.006	0.044	0.010	0.008	0.013	0.011	0.010	0.001	0.003	0.543
Overall solution consistency	*0.802*						*0.885*								*0.864*
Overall solution coverage	*0.929*						*0.764*								*0.543*

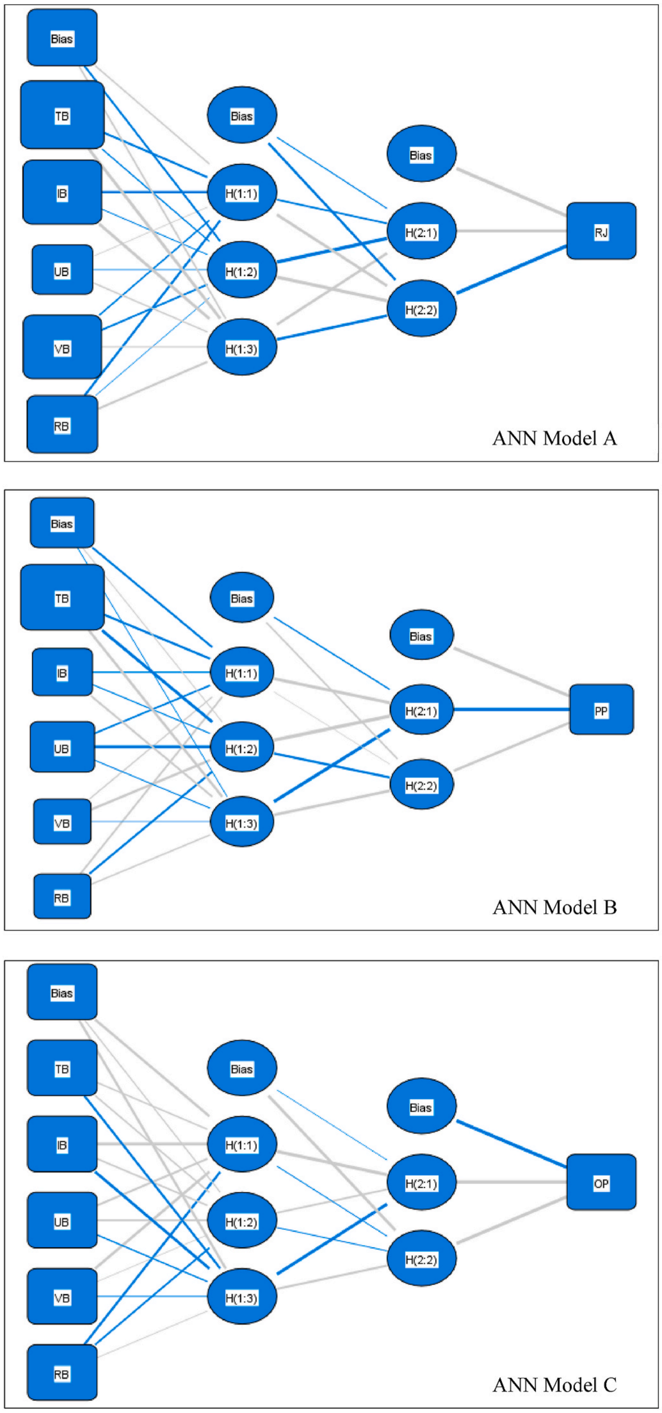
Notes:
1. ✓ represents a high level of condition, while × indicates a low level of condition.
2. Core conditions are boxed (i.e., ☑ or ☒), while peripheral conditions are not (i.e., ✓ or ×).
3. Blank spaces represent the so called "don't care" situation in which the condition can either be present or absent and thus does not have an influence (Mattke et al., 2022).

Theory (Ram, 1987; Ram and Sheth, 1989). Moreover, the results suggest that there is no similar solution for all resistance groups, implying that these resistant mobile consumers behave differently and differ in their innovation resistance. Identically, most of the configurations do not look the same across all groups. This finding corroborates with Laukkanen et al. (2008), who argued that rejecters, postponers, and opponents should be approached differently as they do not behave the same.

Specifically, for rejecters, tradition barrier emerges as a core condition that spans four out of six configurations in the solution, suggesting that a high level of tradition barrier prevails in inducing a high level of rejection. This is especially true in RC1 and RC2, which state that a high level of tradition barrier would result in a high level of rejection even if the value barrier and usage barrier are low. Besides, as seen in RC3 and RC4, the power of tradition barrier would be stronger in predicting a high level of rejection when it is paired with image barrier and risk barrier. This is the case because both RC3 and RC4 are showing incredibly high raw coverage values (i.e., 0.804 and 0.812), which propose that both configurations are highly relevant empirically and exhibit a great explanatory power towards the rejection behaviour (Park et al., 2020) as compared to RC1 and RC2 (showing only a raw coverage value of 0.481 and 0.507 respectively). Interestingly, the ANN analysis echoes the same finding too, as it was found that tradition barrier has the topmost relative importance to the rejection behaviour. It should also be noted that the pivotal role of tradition barrier on the rejection behaviour is identical to the findings of Laukkanen (2016) in a study of mobile banking. Other than tradition barrier, usage barrier is another core condition as seen in RC5 and RC6. Nevertheless, unlike tradition barrier, usage barrier must be grouped with other barriers (i.e., image barrier, value barrier, and risk barrier) for these configurations to work. RC5 reveals that a high level of usage barrier and risk barrier coupled with a low level of image barrier and value barrier would result in a high level of rejection, whereas RC6 requires all barriers (except for tradition barrier) to be high in degree so that a high level of rejection would occur. Given that usage barrier is only strong with other major barriers, perhaps this explains its bottommost ranking in the ANN analysis. Such a trivial role of usage barrier on the rejection behaviour is once again similar to Laukkanen (2016), who found that usage barrier has not much influencing power over the rejection of mobile banking.

Regarding postponers, the fsQCA returns a total of eight configurations, making the interpretation of results challenging. The first three configurations (i.e., PC1 to PC3) involve three conditions, while the rest (i.e., PC4 to PC8) involve four conditions. Given this, it is useful to refer to the complementary results obtained from the ANN analysis. The sensitivity analysis shows that tradition barrier has once again emerged as the most important exogenous construct or condition for the postponement behaviour. This especially supports the results obtained from fsQCA, as tradition barrier is the only core condition that could yield great raw coverage and unique coverage scores when combined with only two other conditions. As can be observed in PC2 and PC3, which both have the highest raw coverage scores across (i.e., 0.547 and 0.557) all configurations for postponers, it is suggested that a high level of tradition barrier, together with a high level of image barrier and risk barrier (i.e., PC2), or coupled with a high level of value barrier and risk barrier (i.e., PC3), would greatly explain the high occurrence of postponement behaviour. PC1 reinforces this finding as it is indicated that a high level of tradition barrier could still result in a high level of postponement even if there is a low level of image barrier and usage barrier. It is also noteworthy to mention that PC1 has the highest unique coverage score, meaning there is only a small explanatory overlap between PC1 and other configurations (Park et al., 2020), attesting that PC1 is a truly unique configuration for the postponement behaviour. Interestingly, this imminent role of tradition barrier on postponement contradicts the results obtained by Khanra et al. (2021), who found that tradition barrier is insignificantly related to the adoption postponement of mobile payment. In this study, four out of five pairs of constructs show non-linearity (as shown in Table F2), including the relationship between tradition barrier and postponement. Perhaps, the data analysis method (i.e., SEM) used by Khanra et al. (2021) has constrained them from discovering the asymmetric and non-linear relationships among constructs, hence limited their further findings.

Besides, PC6 gives a simpler configuration as it is stated that except for tradition barrier, a high level of all other active innovation barriers would explain the high level of postponement, and this configuration has the third highest raw coverage score. In comparison, PC4, PC5, PC7, and PC8 give rather sophisticated results, which might be the reason behind these configurations' low raw coverage scores. In these configurations, it is noticed that when one of the active innovation barriers is high in level and the other three barriers are low, postponement behaviour would still have a high chance of occurrence. Perhaps, this could be explained by the complicated non-linear relationships between the constructs among postponers. Furthermore, such a complicated



Notes:
IB = image barrier
OP = opposition
PP = postponement
RB = risk barrier
RJ = rejection
TB = tradition barrier
UB = usage barrier
VB = value barrier

Fig. 2. Deep learning ANN models.

decision-making process of postponers could be due to the characteristics of postponers, who find the m-commerce applications acceptable but prefer to postpone their adoption decisions until the right time (Kleijnen et al., 2009) as they would like to gather more information or prefer more time to process the information (Szmigin and Foxall, 1998). Since their decisions are not final, it is likely that postponers are showing a rather complicated decision-making process, hence the sophisticated configurations.

Unlike rejecters and postponers, the group of opponents has only a sufficient configuration that results in a high level of opposition. All active innovation resistance barriers are included in the configuration, which states that a high level of all barriers would explain the high level of opposition behaviour. In addition, image barrier, usage barrier, value barrier, and risk barrier are all identified as the core conditions, while tradition barrier is labelled as peripheral condition. Given that a core condition indicates strong evidence for a causal relationship while peripheral condition signifies weaker evidence (Fiss, 2011), it is implied that tradition barrier is not strong in leading to the opposition behaviour compared to other barriers. The ANN analysis supports this as tradition barrier was found to be the least important barrier. Moreover, the results produced by the ANN analysis assert that image barrier is the most important barrier, complementing the rather simple solution yielded in the fsQCA. Nel and Boshoff (2021), in their study of opposition to using digital-only banks, somehow supported the crucial role of image barrier

Table 3
Predictive accuracy of the deep learning ANN models.

Neural networks	ANN Model A ($R^2 = 0.744$) Input neurons: Tradition barrier, image barrier, usage barrier, value barrier, and risk barrier. Output neuron: Rejection						ANN Model B ($R^2 = 0.722$) Input neurons: Tradition barrier, image barrier, usage barrier, value barrier, and risk barrier. Output neuron: Postponement						ANN Model C ($R^2 = 0.773$) Input neurons: Tradition barrier, image barrier, usage barrier, value barrier, and risk barrier. Output neuron: Opposition					
	Training			Testing			Training			Testing			Training			Testing		
	n	SSE	RMSE	n	SSE	RMSE	n	SSE	RMSE	n	SSE	RMSE	n	SSE	RMSE	n	SSE	RMSE
ANN1	322	4.411	0.117	28	0.274	0.099	315	4.026	0.113	35	0.333	0.098	311	5.095	0.128	39	0.525	0.116
ANN2	315	4.187	0.115	35	0.465	0.115	314	3.968	0.112	36	0.324	0.095	316	5.304	0.130	34	0.557	0.128
ANN3	314	4.771	0.123	36	0.535	0.122	317	3.843	0.110	33	0.301	0.096	316	5.110	0.127	34	0.618	0.135
ANN4	317	5.076	0.127	33	0.692	0.145	323	4.089	0.113	27	0.212	0.089	311	5.251	0.130	39	0.545	0.118
ANN5	323	4.062	0.112	27	0.360	0.115	312	3.894	0.112	38	0.368	0.098	307	4.893	0.126	43	0.503	0.108
ANN6	312	4.298	0.117	38	0.323	0.092	305	3.375	0.105	45	0.505	0.106	318	5.011	0.126	32	0.459	0.120
ANN7	305	4.189	0.117	45	0.359	0.089	308	3.906	0.113	42	0.397	0.097	310	5.416	0.132	40	0.312	0.088
ANN8	308	3.912	0.113	42	0.461	0.105	327	3.610	0.105	23	0.137	0.077	314	4.923	0.125	36	0.493	0.117
ANN9	327	4.123	0.112	23	0.412	0.134	315	3.488	0.105	35	0.446	0.113	308	4.766	0.124	42	0.518	0.111
ANN10	315	4.886	0.125	35	0.592	0.130	310	3.579	0.107	40	0.512	0.113	313	5.484	0.132	37	0.615	0.129
Average		*4.392*	*0.118*		*0.447*	*0.115*		*3.778*	*0.110*		*0.354*	*0.098*		*5.125*	*0.128*		*0.515*	*0.117*
Standard deviation		*0.389*	*0.005*		*0.130*	*0.018*		*0.246*	*0.003*		*0.120*	*0.011*		*0.235*	*0.003*		*0.087*	*0.013*

Notes:
1. $RMSE = \sqrt{(1/n) \times SSE}$.
2. According to Leong et al. (2020a), the goodness-of-fit index (R^2) = 1 - Average of RMSE during testing/Average of SSE during testing.

Table 4
The sensitivity analysis.

Neural networks	ANN Model A ($R^2 = 0.744$) Output neuron: Rejection					ANN Model B ($R^2 = 0.722$) Output neuron: Postponement					ANN Model C ($R^2 = 0.773$) Output neuron: Opposition				
	Relative importance					Relative importance					Relative importance				
	TB	IB	VB	RB	UB	TB	UB	VB	RB	IB	IB	VB	UB	RB	TB
ANN1	0.297	0.247	0.243	0.160	0.053	0.384	0.200	0.130	0.126	0.159	0.377	0.292	0.080	0.154	0.097
ANN2	0.255	0.260	0.197	0.159	0.129	0.370	0.224	0.257	0.130	0.019	0.416	0.296	0.075	0.120	0.093
ANN3	0.178	0.421	0.102	0.072	0.226	0.401	0.168	0.270	0.079	0.080	0.449	0.219	0.102	0.144	0.085
ANN4	0.219	0.147	0.178	0.191	0.265	0.490	0.208	0.077	0.210	0.015	0.513	0.266	0.133	0.052	0.037
ANN5	0.340	0.164	0.197	0.186	0.113	0.403	0.201	0.167	0.147	0.081	0.440	0.308	0.072	0.086	0.094
ANN6	0.429	0.217	0.215	0.052	0.087	0.395	0.243	0.167	0.093	0.101	0.428	0.271	0.107	0.096	0.098
ANN7	0.283	0.341	0.315	0.047	0.014	0.426	0.201	0.075	0.172	0.127	0.440	0.281	0.117	0.128	0.033
ANN8	0.296	0.225	0.295	0.141	0.043	0.247	0.225	0.244	0.119	0.165	0.416	0.236	0.138	0.136	0.074
ANN9	0.361	0.255	0.224	0.091	0.069	0.337	0.250	0.197	0.103	0.114	0.363	0.277	0.102	0.126	0.132
ANN10	0.230	0.207	0.286	0.182	0.095	0.472	0.159	0.190	0.061	0.119	0.438	0.283	0.155	0.017	0.107
Average relative importance	*0.289*	*0.248*	*0.225*	*0.128*	*0.109*	*0.393*	*0.208*	*0.177*	*0.124*	*0.098*	*0.428*	*0.273*	*0.108*	*0.106*	*0.085*
Normalized relative importance (%)	*100.0*	*86.0*	*78.0*	*44.4*	*37.9*	*100.0*	*53.0*	*45.2*	*31.6*	*25.0*	*100.0*	*63.8*	*25.3*	*24.7*	*19.9*
Ranking	*1st*	*2nd*	*3rd*	*4th*	*5th*	*1st*	*2nd*	*3rd*	*4th*	*5th*	*1st*	*2nd*	*3rd*	*4th*	*5th*

Notes: IB = image barrier, RB = risk barrier, TB = tradition barrier, UB = usage barrier, and VB = value barrier.

in driving the opposition behaviour. In their study, among other active innovation resistance barriers, image barrier was found to have the strongest influence on negative attitude, which subsequently leads to the intention to oppose. Therefore, it is believed that the ANN analysis could complement the fsQCA by ranking the conditions in terms of their relative importance to the outcomes of interest.

6.2. Theoretical implications

In light of the results, it is believed that this study has made threefold contributions towards the Innovation Resistance Theory and the existing literature on m-commerce applications resistance. Firstly, given that it is rare to see the past studies that employed the Innovation Resistance Theory engaged a hybrid approach combining fsQCA and ANN, this study serves as one of the pioneers that scrutinises the Innovation Resistance Theory through the hybrid fsQCA-ANN approach. Secondly, since it was found that all active innovation resistance barriers matter but are not equally important in triggering the resistance behaviours, this study confirms and enriches the Innovation Resistance Theory as the current literature that employed the Innovation Resistance Theory did not delve into the three distinct forms of resistance behaviour concurrently. Thirdly, through a configurational approach complemented by machine learning, this study enriches the existing literature on m-commerce applications resistance by understanding the complicated resistance behaviours of mobile consumers. This is particularly true as the current state of literature oversimplifies mobile consumers' behaviours and mainly focuses on the symmetric and linear relationships among constructs, ignoring the significance of asymmetric and non-linear relationships.

6.3. Practical implications

Even if all active innovation resistance barriers are important in driving a high level of resistance behaviours, practitioners are suggested to focus more on tradition barrier and image barrier. Together, both barriers make up the psychological barriers, which arise when mobile consumers found conflicts between m-commerce applications and their prior beliefs (Talebian and Mishra, 2018). On the other hand, functional barriers, which comprise usage barrier, value barrier, and risk barrier, are indicating the extent of ease-of-use, benefits, and risks of m-commerce applications (Laukkanen et al., 2007). With that said, practitioners should place more resources to develop strategies that could overcome the psychological barriers, so as to lower the resistance behaviours of mobile consumers.

One possible way to tackle the psychological barriers is to instil a faith of trust into mobile consumers, perhaps through some traditional and physical promotional campaigns, roadshows, or virtually via social media platforms. Specifically, during the physical campaigns or roadshows, practitioners should allow mobile consumers to try the m-commerce applications for free rather than just promoting them abstractly. To this end, practitioners could consider giving live demonstrations to mobile users who present at the event by doing simulations on how to use the m-commerce applications. It is also a great idea if some knowledgeable staff could be there to assist and most importantly, answer any queries on the spot. This would definitely help mobile consumers to clear some of their doubts and negative images on the m-commerce applications, changing their impressions that the m-commerce applications are disrupting their prior beliefs during the live demonstrations. Furthermore, engaging social media influencers to help advertise and promote m-commerce applications should be another feasible method to reach mobile consumers. Such a peer influence process, according to Xiao et al. (2018), has a strong influence over one's beliefs. Hence, functioning as a peer who could understand mobile consumers more, social media influencers shall be able to address the conflicts faced by mobile consumers easily. For instance, livestreaming sessions could be arranged between a social media influencer and his/her followers in order for the social media influencer to have a "heart-to-heart" interaction with the followers about anything related to the m-commerce applications. In this way, the followers could clear their doubts concerning the m-commerce applications and eventually find the m-commerce applications matching their prior beliefs.

Besides, practitioners should seek ways to overcome the functional barriers by improving their m-commerce applications. Particularly, an m-commerce application has to be easy and safe to use, on top of entailing benefits and advantages to lower mobile consumers' resistance behaviours. It is suggested that when designing an m-commerce application, practitioners should always be mindful that it would be good if the m-commerce application only requires basic operations from mobile consumers. For example, some m-commerce applications such as mobile payment require the use of near field communication (NFC) function from smart mobile devices, but some mobile consumers might not be aware of this advanced function and hence do not know how to operate it. This increases the difficulty level as mobile consumers have to learn more things in order to be able to operate the m-commerce applications. Furthermore, practitioners should consider whether their m-commerce applications could offer additional benefits to mobile consumers. Failing to do so would cause mobile consumers to stick with their traditional ways of performing tasks. The additional benefits could be offered, perhaps through rewards and membership system. For instance, to encourage the use of mobile ride-hailing, practitioners could consider having different levels of discounts on fares based on the membership levels. A higher membership level would be able to enjoy more discounts on fares and vice versa. Last but not least, the earlier suggestions of having promotional campaigns and engaging social media influencers shall also aid in disseminating information that the m-commerce applications are safe to use, hence lowering the risk barrier of mobile consumers. Moreover, running advertisements on mobile social media platforms in the form of video could help reduce the risk barrier for mobile consumers. This could be more effective if the promotional videos are produced by social media influencers who are truly an expertise in that area, as the credibility of social media influencers would instil trust into their followers, lowering their perception of risks eventually (Leite and Baptista, 2022).

7. Limitations and recommendations

There are some limitations that should be aware of in this study. Firstly, as the data was gathered from a developing nation with a high level of mobile penetration rate but facing a low adoption rate of m-commerce applications, it is possible that the results could not be generalised to other nations (e.g., underdeveloped) with a low level of mobile penetration rate. Therefore, it would be interesting to study if there are any differences among nations, especially between underdeveloped, developing, and developed nations. Secondly, this study is a cross-sectional study that ignores the effects of time, which could alter mobile consumers' resistance behaviours (Venkatesh et al., 2021). Hence, it would be a good idea to probe into the temporal differences and investigate how time affects mobile consumers' resistance behaviours. Thirdly, given that this study aims to clarify the three distinct forms of resistance behaviour exhibited by mobile consumers, this study did not explore much other active innovation resistance barriers that could affect the resistance behaviours (Joachim et al., 2018). As such, scholars are encouraged to explore other active innovation resistance barriers further to see if they could affect the three distinct types of resistance behaviour. Last but not least, the possible effects of demographic variables were excluded from the hybrid analysis. Since it is possible that some of the demographic variables could enhance our understanding of the resistance behaviours, further studies are suggested to include demographic variables in their fsQCA or ANN analysis.

8. Conclusion

M-commerce applications are revolutionising the world, resulting in completely different mobile consumer behaviours that deserve immediate investigations. In view of this and given that understanding the resistance behaviours of mobile consumers towards m-commerce applications is just as crucial as understanding their adoption behaviours, this study built an asymmetric and non-linear model that clarifies the three distinct forms of resistance behaviour exhibited by mobile consumers towards m-commerce applications. To achieve this purpose, a hybrid analysis that combines fsQCA and ANN was engaged to reveal the complicated asymmetric and non-linear relationships among the active innovation resistance barriers and resistance behaviours. Reflecting on the results, this study believes that it is imprecise to oversimplify the resistance behaviours of mobile consumers by assuming that they would exhibit the same resistance behaviour and, therefore, share the same decision-making process. Instead, depending on their resistance behaviours, mobile consumers would evaluate and prioritise the active innovation resistance barriers differently in their decision-making process. Scholars are, therefore, advised to recognise the distinct forms of resistance behaviour, so as to further advance the existing state of knowledge. Hopefully, this study could encourage and inspire more research on the complicated resistance behaviours of mobile consumers towards m-commerce applications and perhaps, other innovations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jretconser.2023.103526.

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